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Assessing above-ground biomass of open-grown urban trees: a comparison between existing models and a volume-based approach

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Abstract

Assessment of the amount of carbon and the value of ecosystem services provided by urban trees requires reliable data. Predicting the proportions and allometric relationships of individual urban trees with models developed for trees in rural forests may result in significant errors in biomass calculations. To better understand the differences in biomass accumulation and allocation between urban and rural trees, two existing biomass models for silver birch (Betula pendula Roth) were tested for their performance in assessing the above-ground biomass (AGB) of 12 urban trees. In addition, the performance of a volume-based method utilizing accurate terrestrial laser scanning (TLS) data and stem density was evaluated in assessing urban tree AGB. Both tested models underestimated the total AGB of single trees, which was mainly due to a substantial underestimation of branch biomass. The volume-based method produced the most accurate estimates of stem biomass. The results suggest that biomass models originally based on sample trees from rural forests should not be used for urban, open-grown trees, and that volume-based methods utilizing TLS data are a promising alternative for non-destructive assessment of urban tree AGB.

Key words: Remote sensing; Trees outside forests; LiDAR; Street trees

Introduction

Trees and other green infrastructure provide the urban environment with various ecosystem services (Gómez-Baggethun and Barton, 2013), such as noise reduction (Bucur, 2006), storm water management (Valtanen et al., 2014), air pollutant removal (Setälä et al., 2013; Morani et al., 2011), and improvement of aesthetic beauty (Hauru et al., 2015). In recent years, applications such as iTree (iTree, 2015) have rendered it possible to evaluate tree-derived ecosystem services based on tree characteristics in an urbanized setting (see, e.g., Baró et al., 2014; Nowak, Hoehn et al., 2013).

However, the majority of the studies addressing ecosystem services provided by urban trees are based on city- or regional-scale models, whereas local-scale empirical urban data is needed to estimate, e.g., the influence of roadside trees in ecosystem service provision (Pataki et al., 2013; Pataki et al., 2011). An ecosystem service related to this study is sequestering and storing of atmospheric carbon, through which urban trees both locally and globally affect the carbon cycle and thus the mitigation of climate change (Nowak and Crane, 2002). It has been estimated that the terrestrial biosphere, consisting mainly of forests, accounts for approximately 45% (1.4 Gt) of the global sequestration of atmospheric carbon annually (Schimel et al., 2001). Davies et al. (2011) showed that the contribution of urban forest to nationwide carbon storage can also be considerable, especially in countries with low overall forest coverage. Moreover, FAO classifies urban trees and forests as being part of a larger group encompassing trees outside rural forests (de Foresta et al., 2013). Following the FAO classification, Schnell et al. (2015) studied forest monitoring data from 11 countries on three continents and showed that on average over 10% of the countries' tree biomass actually accumulates outside rural forests. The figure mainly consists of urban forests as well as scattered and other non-forest trees on agricultural land. Still, urban tree-specific allometric models for biomass assessment are scarce and thus little is known how general models perform in an urban environment.

The traditional means for accurately assessing the aboveground biomass (AGB) of a tree is based on weighing the aboveground parts of the tree, quantifying the relative amounts of stem wood and branches, and defining the dry biomasses of both components. Since the procedure is destructive, i.e., it requires cutting down the specimen, the aim of the procedure is most often to construct an allometric biomass model from a sample of trees. The model is then used to estimate the biomass for the local tree population. Various species-specific models have been proposed for assessing the biomass of single trees (see, e.g., Yoon et al., 2013; Ter-Mikaelian and Korzukhin, 1997). The use of these models is commonly based on easily obtainable measurements, like diameter at breast height (DBH) and tree height. The main shortcoming of model-based biomass assessments is that the target population should resemble the one used for creating the model. This is especially problematic in urban tree populations whose growth conditions and thus biomass allocation patterns can differ from the environment where the biomass models were created (see, Dahle et al., 2014; Poorter et al., 2012; Niemistö, 1995). Furthermore, the use of traditional biomass modelling procedures is rarely applicable in urban inventory projects simply due to the fact that destructive sampling is rarely an acceptable solution in the urban environment. Hence, alternative ways of acquiring field reference data for urban tree-specific biomass are sought.

During the last decade, various laser scanning (LS) methods enabling the use of precise three-dimensional (3D) information on, e.g., urban space and infrastructure have become an essential tool in urban mapping and planning (Kukko et al., 2012; Pu and Vosselman, 2009; Pfeifer et al., 2007). Terrestrial laser scanning (TLS) is a stationary method for collecting detailed 3D data. The scanner emits millions of laser pulses and records the back scattering echoes. Based on accurate range and angle measurements, the data are processed into point clouds that can be thought of as detailed 3D images of the scanned objects. In TLS, the scanner is typically mounted on a tripod at a height of approximately 2 m. The resulting point clouds enable detailed modelling of, e.g., building facades (e.g., Zhu et al., 2011; Haala et al., 2008) and tree stems (Liang et al., 2014; Holopainen et al., 2013). The point clouds can be used to model entire trees with high precision to the level of single branches, which enables accurate dimension and volume measurements of virtually any visible part of the tree (e.g., Raumonen et al., 2013; Maas et al., 2008). Utilization of TLS data in assessing AGB has been studied in both rural (Hauglin et al., 2013; He et al., 2013; Kankare et al., 2013, Yu et al., 2013) and urban surroundings (Vonderach et al., 2012) by enhancing and localizing the existing biomass models. Combining the TLS-derived volume estimates with species-specific basic densities of wood and bark paves the way for an alternative method of estimating tree AGB without having to cut down the tree (see, e.g., Yu et al., 2013; McHale et al., 2009). A non-destructive method would enable gathering of large tree-level reference datasets, e.g., for executing remote sensing-based biomass inventories or creating tree-specific biomass models. Such methods would be useful especially in the urban environment where adequate destructive sampling is not applicable.

The aims of this study were twofold. Firstly, we wanted to investigate the performance of two allometric biomass models (Repola, 2008; Muukkonen, 2007) for silver birch (*Betula pendula* Roth) under semi-open urban conditions on roadsides. We hypothesized that (I) models based on trees sampled from rural forests will provide biased biomass estimates in semi-open urban surroundings. The hypothesis was tested separately for stem, branches, and total AGB. Secondly, we wanted to explore the possibility of measuring tree-level reference AGB using TLS-based volume measurements and a priori knowledge about species-specific basic densities. Our second hypothesis was that (II) the TLS-based method outperforms the existing biomass models when estimating AGB for semi-open-grown urban trees.

Materials

The study area is located in the city of Helsinki, Finland (60°10′15″N, 024°56′15″E, Fig. 1). The area represents a typical urban growth environment for roadside trees. The grassy ground surface is bordered by paved surfaces on two sides. The area was built in the 1960s and the majority of the roadside trees also originate from that time. However, some damaged or dead trees have been replaced during the years. The trees used for the biomass estimation were 12 silver birches aged approximately from 20 to 55 years. The trees were cut down because of a construction project in August 2014, which allowed us to measure an accurate reference biomass for each tree.

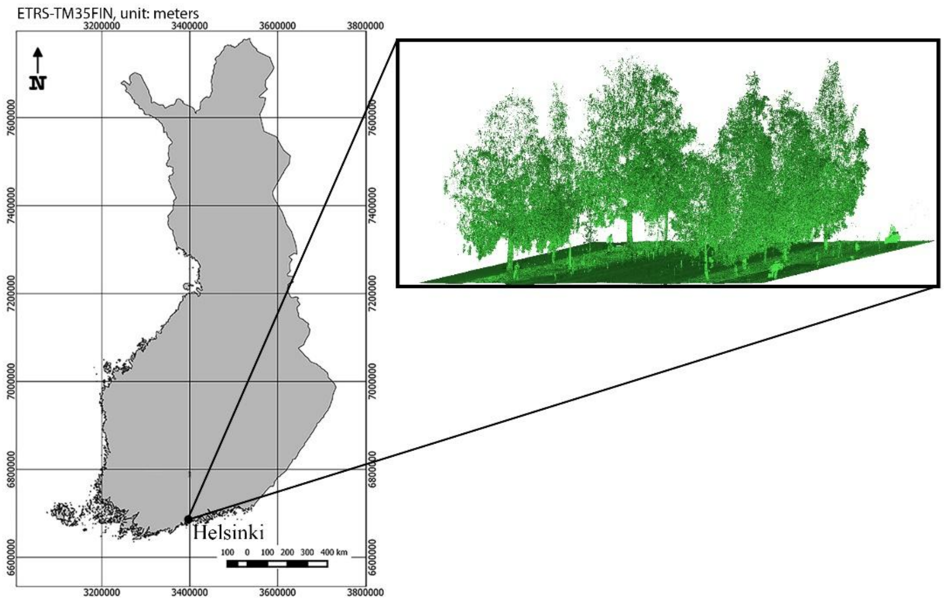

Figure 1. Illustration of the study area in the city of Helsinki in southern Finland. In upper right a road section with standing roadside trees visualized as TLS point cloud.

Tree DBH and height were measured manually from the point clouds. The DBH was determined as a mean of two perpendicular measurements, whereas the tree height was determined from the highest laser hit in the point cloud. The DBH of the study trees ranged from 13.5 to 32.8 cm and height from 11.0 to 18.3 meters. The trees were primarily exposed to full sunlight (Fig. 2). Growing in a single row with an average spacing of 7.5 meters, the trees were shading each other on two sides (SE-NW-direction). However, there was no shading by buildings and the distance to the nearest trees on the opposite side of the road (SW-direction) was over 16 meters. Hence, the sample roadside trees were considered semi-open grown.

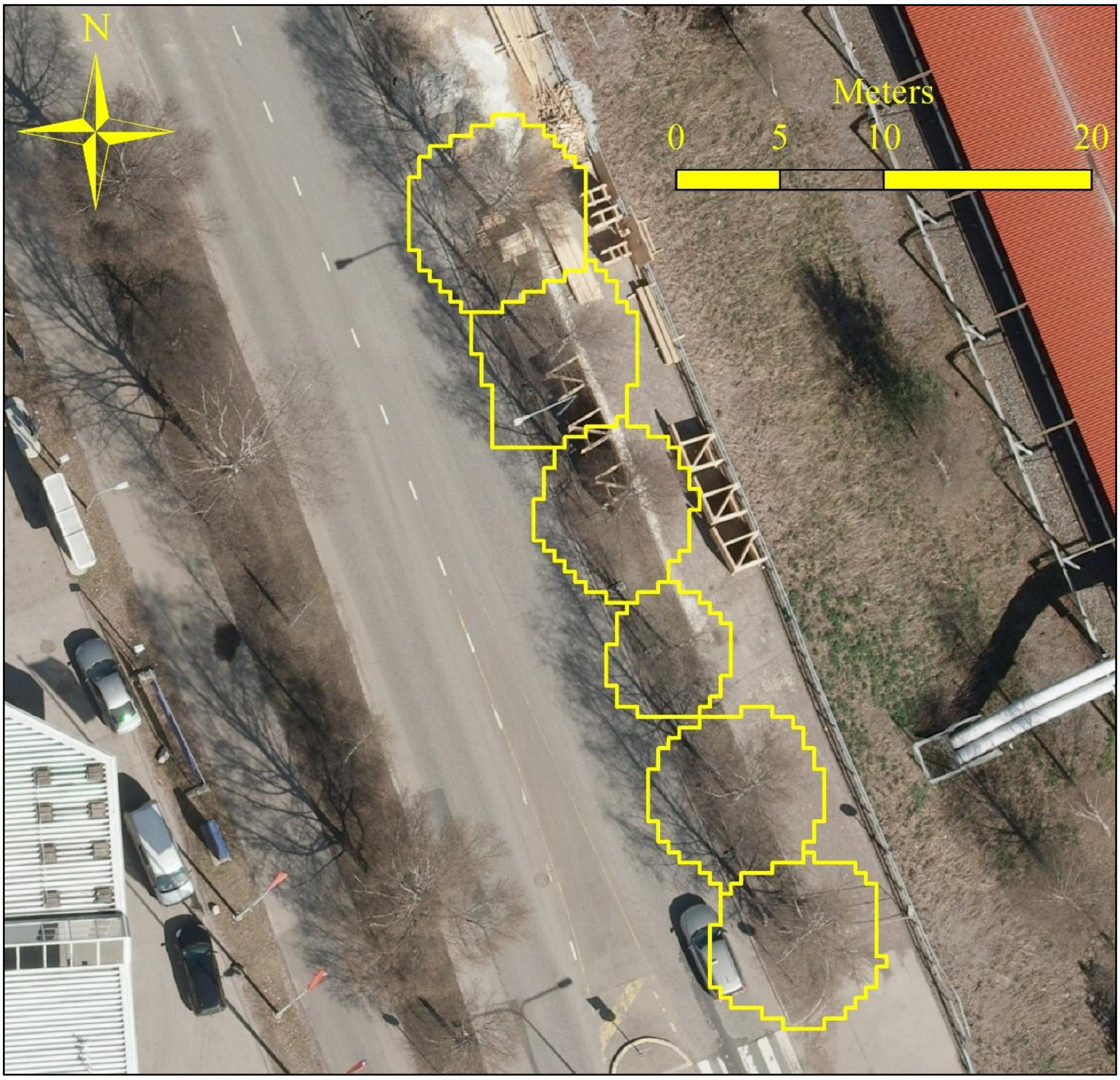

Figure 2. Aerial photograph from the study area visualizing part of the study area. The study trees in the picture are highlighted in yellow.

The TLS data for the 12 birch trees were collected in August 2014 using the Z+F IMAGER5006h laser scanner with a nominal point spacing of 1.6 mm at 10 m. Because of the rather narrow street space, optimal scanning geometry could not be achieved, which was compensated by increasing the number of scanning locations. Altogether, the research area was covered with 35 scans which were co-registered using reference targets and Leica TCRP1203 tachymeter. The principle of co-registering is to detect reference targets from the point clouds, which allows aligning the point clouds in the same coordinate system. In this study, flat reference targets were positioned on both sides of the road. For a more detailed description of co-registration with reference targets, see, e.g., Kankare

(2015). The registration accuracy of the final point cloud was approximately 5 mm (Fig. 3). The scannings were made during the growing season with each tree in full foliage, which greatly affected how well individual branches and upper parts of the stem could be discerned.

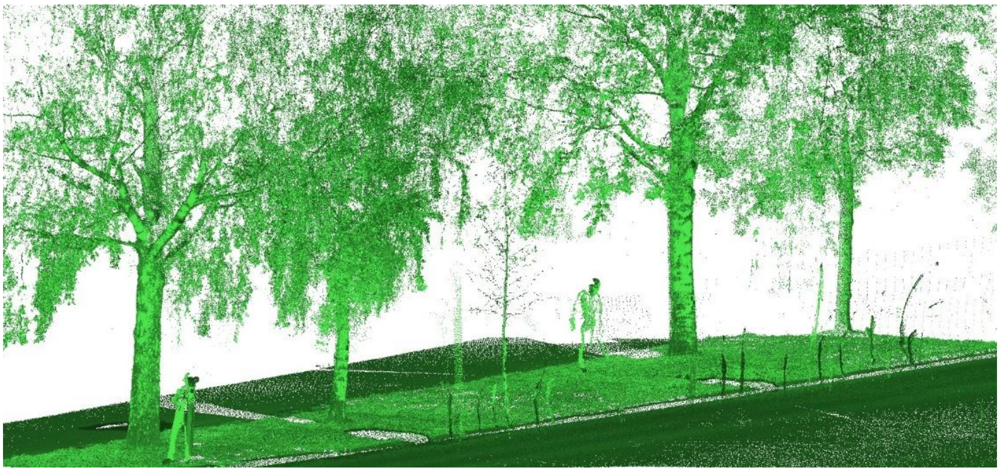

Figure 3. Sample of the final co-registered TLS point cloud before extraction of individual stems.

Methods

Reference AGB

For obtaining the reference AGB, every study tree was weighed. The trees were cut the following day after the acquisition of the TLS data. All trees were separated into stem and branches. Some of the tree tops had been damaged during the felling, which affected the separation. Hence, the stem was separated from the branches up to the diameter of 0-3 cm, i.e., as high as it was possible to follow the tapering stem. Both stem and branches were weighed separately using Dini Argeo TLN300 (Modena, Italy, 5 g divisions) scales. The branch section included foliage. In order to define the average moisture content of the trees, a 5-cm sample disc from the stem and three 10-cm samples from the branches were taken from two randomly selected trees. The stem sample discs were taken from one-meter height whereas the branch samples were cut near the stem from three different heights (the lowest, the middle, and the uppermost third of the crown). Moisture contents of the stem wood and stem bark were determined by measuring the fresh and dry masses of the wood and bark from the sample disc with Precisa XT4200C (Dietikon, Switzerland, 0.01 g divisions) precision scales. The dry mass was measured after drying the samples in 103 °C for three days. Moisture content was calculated according to Formula 1. The total stem dry biomass was determined by first evaluating the proportions of stem bark and stem wood according to Ilvessalo (1948) and then multiplying the fresh masses of stem wood and bark by their dry matter contents (Formula 2). When defining the moisture content of branches, the effect of foliage was ignored. Because the leaves tend to have higher moisture content than that of branches (e.g., Kärkkäinen, 2007), the total branch dry weight was thus overestimated slightly.

$$\textit{Moisture content} = \frac{M_f - M_d}{M_f}, \quad (1)$$

$$\textit{Stem dry biomass} = M_f * (1 - \textit{Moisture content}), \quad (2)$$

where M_f stands for fresh weight and M_d for the dry weight.

Assessment of AGB using existing models

AGBs of individual trees where estimated using the best models by Repola (2008) (referred to as Model 1; see Appendix 1 for more details) and Muukkonen (2007) (referred to as Model 2; see Appendix 2 for more details). Model 1 is a multivariate linear model based on 127 field-measured trees (see, Repola, 2008) and uses DBH and height as explanatory variables. It consists of six separate equations: stem wood, stem bark, living branches, dead branches, total AGB, and foliage. For Model 1 the total AGB was estimated using a specific equation whereas estimates for stem and branch biomasses were achieved by combining several equations. The stem biomass estimate was achieved by summing up the estimates for stem wood and bark. Similarly, the estimate for branch biomass was the sum of living and dead branches, and foliage.

Model 2 is a generalization of multiple biomass equations presented in previous studies (see, Muukkonen, 2007) and uses DBH as an explanatory variable. It consists of three separate equations:

stem, branches, and foliage. The estimates for stem biomass were obtained using a specific equation. The total branch biomass was achieved by summing up the estimates of branch and foliage biomasses. Finally, the total AGBs were calculated by summing up both stem and total branch biomasses. Although not clearly stated in the original articles (Muukkonen, 2007; Repola, 2008), we presumed that both Model 1 and Model 2 referred to the stem with no limiting upper diameter.

Assessment of biomass using TLS-based approach

Because of the unfavorable scanning conditions, branch biomass could not be derived from the TLS point clouds. Full foliage blocked the laser pulses from entering the crown and only the biggest branches in the lowest crown parts were distinguishable. Hence, using the TLS-based approach, the biomass was assessed only for the stem. TLS point clouds were separated for each tree and manually classified so that points from tree stems were separated from those of branches. Stem diameters were automatically derived for each stem at 0.125, 0.5, 1.0, 1.3, and 1.5-meter heights, and then for every 0.5-meter distance up to 60% height of the stem (Fig. 4). The height limit was used because dense foliage greatly decreased the amount of laser pulses reflecting from the stem in the upper parts of the trees. For most trees, stem diameters could not be derived above 60% height. Two different methods were tested for deriving stem diameters from different heights. In the first approach, the diameters were derived by fitting a circle into the stem point cloud at each height interval in R software using least-square method. The obtained D_{circle} estimates were considered as average diameters for each log and were used as such when determining the volume of the logs. In the second approach, the D_{circle} values were utilized to fit a spline curve describing the stem diameter D_{spline} at each height interval. The aim of the second approach was to smooth the effects of estimation errors of D_{circle} especially in the upper parts of the stem. Spline curves were fitted to D_{circle} estimates with *smooth.spline* function in R software (R Development Core Team, 2015) in order to create stem curves for the study trees. By setting the spline function smoothing parameter *spar* to 0.6, the fit was adjusted so that diameters were not allowed to grow from the bottom of the tree to the top. The parameter *spar* indicates the weight of individual diameter measurements in fitting the spline curve.

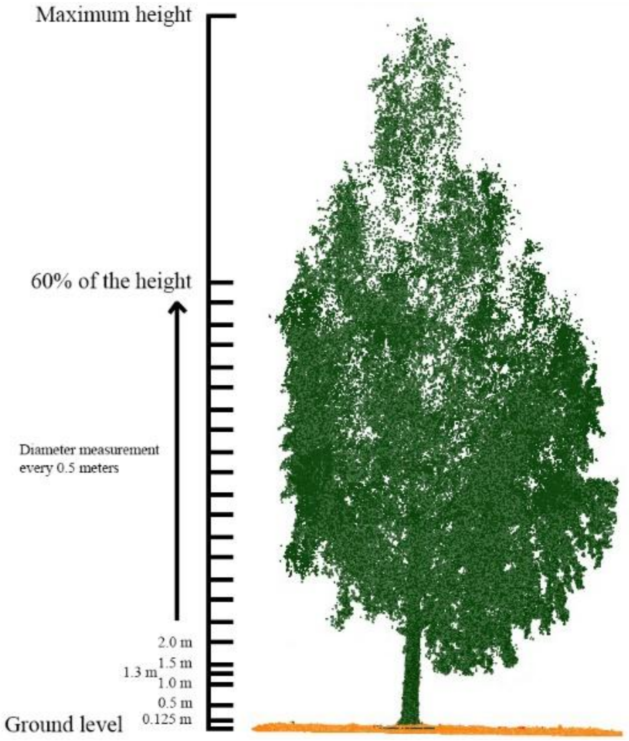

Figure 4. A sample point cloud with specified heights for measuring diameter.

The volume of the lower 60% of the stem was determined using the Huber formula (Formula 3)

$$V = \sum_{i=1}^{j} d_i * h_i, \tag{3}$$

where d_i is the diameter of the log at the middle and h_i the length of the log. For each trunk, separate volume estimates were determined using D_{circle} and D_{spline} diameters. The upper part of the stem was assumed to be the shape of a cone (Formula 4).

$$V = \frac{1}{3}\pi\left(\frac{d}{2}\right)^2 h, \tag{4}$$

where h is the height and d is the bottom diameter of the cone both measured from the TLS point cloud.

The estimated total volumes were converted to dry biomass by multiplying total volume by species-specific basic density. A reliable determination of the average basic density of a tree requires multiple measurements from a large number of stems (see, e.g., Repola, 2006). Since there were no studies available concerning the basic density of urban silver birch, the basic density was adopted from literature concerning rural silver birch, with tree age and site type taken into consideration. In this study, the basic density of 488 kg/m^3 was used for birch stem wood and the effect of stem bark and inner branches on total stem density was accounted for by multiplying the basic density of stem wood by 1.015 (Hakkila, 1979).

Accuracy assessment

The model-based biomass estimates for stem wood, branches, and total AGB were compared with reference measurements. In addition, relative amounts of observed and modeled branch biomasses (Formula 5) were examined. As the TLS-based methods did not include crown biomass, the accuracy was evaluated by comparing the estimates to reference measurements of stem biomass. Also, the TLS-based estimates were compared to the stem biomasses derived from the existing allometric models. Comparisons between the variables were made using root mean square error (RMSE) (Formula 6) and bias (Formula 7).

$$branch\ biomass\ \% = \frac{100 * M_b}{M_{tot}}, \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}}, \tag{6}$$

$$bias = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n}, \tag{7}$$

where M_b is the dry mass of branches, M_{tot} the total dry AGB, n the number of observations, y_i the observed value and $\hat{y}_i$ the predicted value.

Hypotheses I and II were tested by comparing the estimated mean values to the reference mean value with pair-wise t-test using 95% confidence level. The null hypothesis was that the estimate mean values do not differ from the reference mean values. The significance of the biomass estimates from Model 1 and Model 2 was also tested in order to verify the differences between the two allometric models.

Results

The average moisture contents for stem wood and stem bark were 40.7% and 30.2%, respectively. The combined moisture content for stem and bark was 38.9%. For branches, the combined moisture content of branch wood and bark was 41.9%. A summary of reference dry biomasses for branch, stem, and total AGB is presented in Table 1.

Table 1. Field-measured fresh biomasses of the separate constituents of silver birch individuals converted to dry biomass (n=12)

	Min (kg)	*Max (kg)*	*Mean (kg)*
Stem	31.9	287.0	179.7
Branches	21.9	273.2	127.7
Total	53.8	528.0	307.3

When compared to the reference data, both tested models resulted in biased estimates when applied to urban roadside trees (Table 2). For the two models, the branch biomass was heavily underestimated whereas the stem biomass was overestimated. On average, the reference branch ratio of the study trees was 40.6%, whereas the estimates from Model 1 and Model 2 suggested ratios of 23.8 and 20.3, respectively. When evaluating the significance of the differences between the two allometric models, the differences were significant for both branch and stem biomasses (p-values 0.003 and 0.002, respectively), but not for total AGB (p-value 0.054)

Table 2. Tree-level accuracy of existing biomass models in terms of RMSE and bias. Negative values in the bias column indicate underestimation and positive ones overestimation. The % column shows the values in relation to the reference mean values.

	Branches				Stem				Total AGB			
	RMSE (kg)	*%*	*bias (kg)*	*%*	*RMSE (kg)*	*%*	*bias (kg)*	*%*	*RMSE (kg)*	*%*	*bias (kg)*	*%*
Model 1	76.8	60.1 %	-58.3	-45.6 %	40.3	22.4 %	36.0	20.0 %	66.2	21.6 %	-32.1	-10.5 %
Model 2	85.8	67.2 %	-66.1	-51.8 %	59.3	33.0 %	55.9	31.1 %	65.4	21.3 %	-10.3	-3.3 %

Tree-level accuracies of the stem biomass estimates acquired with the two TLS-based methods are presented in Table 3. TLS refers to the biomasses calculated with D_{circle} diameters and TLS_{fitted} to those calculated with D_{spline}.

Table 3. Accuracy of the two TLS-based stem biomass estimates in terms of RMSE and bias. Negative values in the bias column indicate underestimation and positive ones overestimation. The % column shows the values in relation to the reference mean values.

	Stem			
	RMSE (kg)	*%*	*bias (kg)*	*%*
TLS	19.77	11.0	-9.8	-5.5
TLS_{fitted}	12.10	6.7	-0.7	-0.4

Of the two TLS-based methods, TLS_{fitted} resulted in more robust estimates. Thus, the final comparison between different approaches was done between Model 1, Model 2, and TLS_{fitted}.

The model-derived branch, stem and total dry biomasses are plotted against reference dry biomasses in Fig. 5. The plots show that stem biomass is overestimated with both models whereas branch biomass is underestimated. For comparison, the TLS-based estimates (TLS_{fitted}) correspond much better to the reference stem biomass.

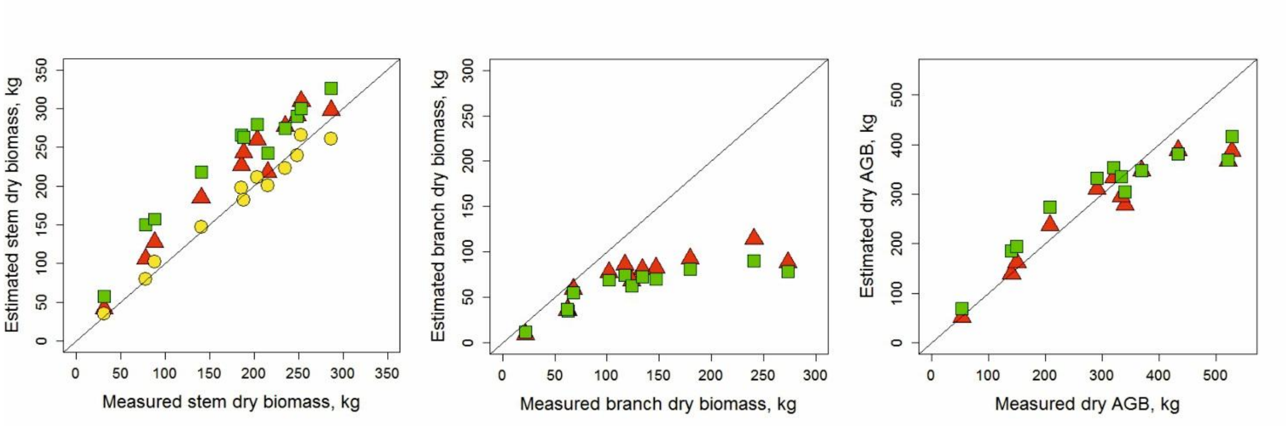

Figure 5. Estimated stem biomass (left), branch biomass (middle), and total AGB (right) plotted against field reference. Triangles (red) represent the estimates from Model 1, squares (green) the estimates from Model 2, and circles (yellow) the TLS-based (TLS_{fitted}) estimates (only for stem).

For both branch and stem biomasses, the reference biomass differed significantly (95% confidence interval) from the biomasses estimated with Models 1 and 2. However, when the estimated biomasses were aggregated into total AGB, the difference was not significant. Considering the TLS-based estimates of stem biomass (only method TLS_{fitted} was tested), statistically significant differences between the reference and the estimates could not be found. The results of the statistical analysis are presented in Table 4.

Table 4. Statistical analysis of differences in Stem, Branch and total AGB. Column t-value shows the result of a pair-wise t-test, df the degrees of freedom, and p-value the statistical significance of the result. The tested null hypothesis was that there is no difference in the measured and observed mean biomasses.

	Branches			Stem			Total AGB		
	t-value	*df*	*p-value*	*t-value*	*df*	*p-value*	*t-value*	*df*	*p-value*
Model 1	-4.015	11	0.002	9.267	11	< 0.0001	-0.527	11	0.609
Model 2	-3.868	11	0.003	6.611	11	< 0.0001	-1.373	11	0.197
TLS_{fitted}	-	-	-	-0.188	11	0.854	-	-	-

In Fig. 6, the tree-level biases of estimated biomasses are plotted against DBH. These plots likewise indicate that both tested models overestimate stem biomass and underestimate branch biomass. Moreover, it seems that the underestimation of branch biomass increases strongly with DBHs over 27 cm. The accuracy of TLS-based assessment of stem biomass seems to remain rather good across all diameters.

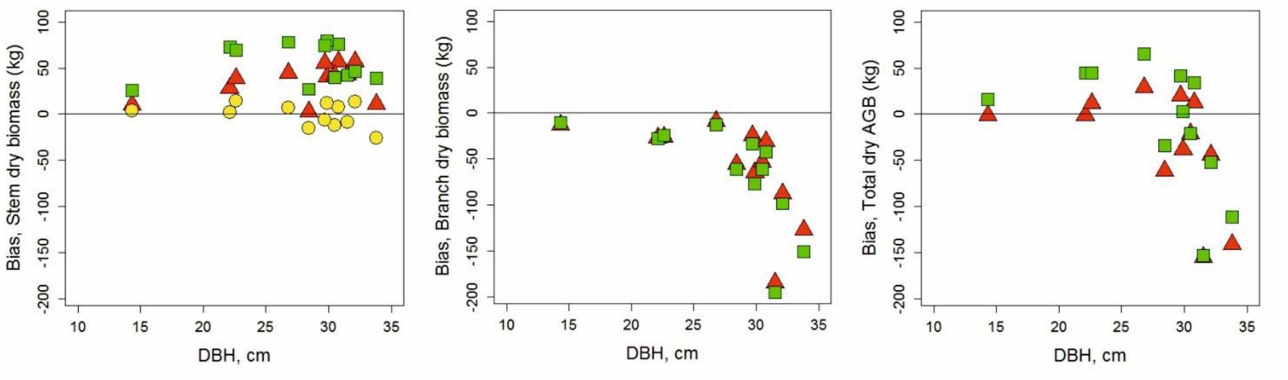

Figure 6. Tree-level bias of estimated stem biomass (left), branch biomass (middle), and total AGB (right) plotted against DBH. Triangles (red) represent the estimates from Model 1, squares (green) the estimates from Model 2, and circles (yellow) the TLS-based (TLS_{fitted}) estimates (only for stem).

Discussion

In this study, we evaluated the applicability of two species-specific allometric biomass models, derived from rural forest-grown trees, in urban roadside surroundings. Because validating of biomass models requires destructive measurements, the size of the field sample was rather small (n=12) and it was measured from a very limited area. Considering the difficulty of gathering sample trees for destructive measurements in an urban environment and the per species amount of sample trees used in the previous studies on urban tree biomass (e.g., Yoon et al., 2013, Vonderlach et al., 2012), the sample size can be considered acceptable. Also, the light conditions on the study site (i.e., considerable shading only from the neighboring trees) are common for the majority of roadside trees outside city centers. Hence, the small sample represents the overall light conditions of the roadside trees rather well. Still, the limitations in the sample size and spatial extent have to be acknowledged when evaluating the applicability of the results. Another factor affecting the quality of the reference data was the separation process of stem and branches. For most trees the stem was separated up to diameters under 1 cm. Still, for some of the biggest trees the broken tops made it impossible to follow the tapering stem to diameters under 3 cm. This affected the reference biomasses so that a small amount of stem biomass was transformed into branch biomass. However, as the largest trees were the only ones with broken tops, the relative difference in branch and stem biomasses was considered negligible.

Considering hypothesis I, the results showed that estimates of stem and branch biomasses were biased for Model 1 and Model 2. In the case of Model 1, the magnitude of underestimation of branch biomass was large enough to under-estimate AGB by 10%, even though the stem biomass was overestimated by 20%. As for Model 2, underestimation of branch biomass was even greater but the bigger overestimation of stem biomass resulted in a fairly unbiased estimate for total AGB. Although branch and stem biomass estimates were biased for both Models, the aggregated total AGBs were not significantly different from the reference. According to the results, the accuracy of biomass estimates derived from both models decreases with increasing DBH (Fig. 6). As the bias of stem biomass estimates seems rather invariant across all DBHs, the bias of branch biomass estimates increases rapidly for DBHs over 27 cm.

In analyzing the differences between Model 1 and Model 2, the estimates derived with Model 1 proved more accurate for determining branch and stem biomasses. However, in the case of total AGB the difference between the estimates from the two models was not statistically significant. As stated in the model description, Model 1 used DBH and height and Model 2 only DBH as explanatory variables. It has been shown that the total AGB can be predicted relatively reliably using just the DBH as an explanatory variable (West et. al., 1997, 1999; Zeng and Tang, 2011). For the total AGB, our results support the previous findings. However, when dividing the AGB into branch and stem components, the accuracy is increased when the height information is added into the model.

In terms of applicability of forest-derived biomass models to urban trees, results from previous studies are somewhat conflicting. Nowak (1994) found that when applied to urban open-grown trees, forest-derived models overestimate AGB up to 25%. However, Jo and McPherson (1995) found evidence that this linkage is not necessarily that straight-forward; for some tree species the biomass was underestimated by up to 50% but for others overestimated by up to 45%. Similarly, McHale et al. (2009) found evidence that the performance of forest-derived models varies greatly when applied to urban trees and that their explanatory power varies throughout DBH classes. More recently, Yoon et al. (2013) found that single tree biomass was overestimated when allometric biomass models from natural or artificial stands were applied to urban trees.

We presume that the underestimation of branch biomass as well as overestimation of stem biomass are caused by differences in the allometric relations of the study trees and the sample trees used for building Models 1 and 2. Light conditions are likely to have a significant effect on the allometrics (e.g., Mäkinen 2002; Niemistö, 1995). Although applicable for the study area in terms of vegetation type and climatic factors, the two models are not designed to handle trees from different light conditions. Including variables describing the light conditions indirectly through crown size (e.g., crown width and height) would likely improve the models' performance in urban surroundings. In addition to differing allometrics, the data suggest that the underestimation of AGB would be even greater for trees with DBH over 35 cm. However, since the reference data is limited and does not cover trees with DBHs over 35 cm, this should be further examined with larger reference trees.

Considering hypothesis II, the scanning conditions made it impossible to measure the total volume of the branches. Hence, without an estimate for the branch biomass the total AGB could not be assessed from the data. Still, the stem biomass estimates from TLS_{fitted} were compared to the corresponding estimates from Model 1 and Model 2. The results show that the TLS-based method provided more accurate estimates for stem biomass (Table 3): the RMSE and bias were lower than those obtained for Models 1 and 2. The estimates from TLS_{fitted} were not significantly different from the reference biomasses, whereas for Model 1 and Model 2 significant differences were observed. Comparable studies utilizing TLS for assessing urban tree biomass are rather scarce. Vonderlach et al. (2012) utilized the voxel-based method for estimating the volume and carbon content of entire urban trees and reported an average bias of 2.3% for the tree volume including branches. As the two TLS-based approaches utilized basic density in transforming fresh volume into dry biomass, the methods are sensitive to changes in the basic density value used. In this study, the value for basic density was adapted from previous studies in terms of site fertility and tree age. However, this measure is known to vary significantly between trees of the same species (Heräjärvi, 2004) and also within single trees (Hakkila, 1966). To account for this variability, site- and species-specific basic density could be measured for the trees along with other field data. In the case of acquiring a reference biomass, this would mean, e.g., the use of samples extracted from a number of trees among the reference. Another critical parameter concerns the TLS_{fitted} method, where individual diameter measurements are used to produce the final shape of the stem (i.e., stem diameters at certain heights) with a spline function. Changes in the fitting parameter *spar* affect the shape of the estimated stem curve (i.e., the estimated form of the stem) and thus also the predicted stem volume.

In addition to stem biomass, a thorough estimate of a single-tree AGB would also include branches and foliage. The quality of our data was not high enough for acquiring such detail and hence, the TLS-based methods were only tested for predicting stem biomass. Using the TLS-based method (i.e., combining measured volume and a priori species-specific basic density) for acquiring branch biomass would require dense and accurate point coverage for all branches throughout the height of the tree. Due to the scanning conditions in the current study (especially the leaves partly blocking the laser pulses from reaching the inner parts of the crown), our data failed in capturing the branch structure of the trees. However, as the trees are rarely completely still and the branches themselves block laser pulses from reaching the innermost parts of the crown, acquiring a precise 3D point cloud including even the smallest branch tips is very challenging in field conditions even if the trees have no foliage (see, e.g., Hackenberg et al., 2014; Moskal and Zheng, 2012). Hence, acquiring the branch biomass estimates by directly measuring the volume of the branches seems challenging. Nevertheless, the study shows that in order to model the stem and branches, the TLS data should be collected in leaf-off conditions whenever possible.

Although in the current study stem biomass was estimated using TLS data, the volume-based methods could be applied for mobile laser scanning (MLS) datasets as well. Compared to TLS, collecting MLS data is faster, which lowers the costs of the data. MLS datasets have been used successfully for mapping locations and diameters for individual trees (Liang et al., 2014; Holopainen et al., 2013). TLS- or MLS-based tree-level reference biomass can be used in multi-step approaches where the sample data is generalized for the study area with coarser remote sensing data, e.g., airborne laser scanning (ALS) and statistical methods (see e.g., Saarinen et al., 2014; Tanhuanpää et al., 2014). In an efficient operative inventory system, an extensive teaching data could be collected with MLS system and generalized for all trees in the inventory area using ALS data. Alternatively, the method could be used for acquiring large reference data for the needs of allometric modeling, which would otherwise be unattainable using destructive methods.

Conclusions

In this study we tested the performance of two allometric biomass models in assessing biomass of 12 semi-open-grown urban roadside trees. We also investigated the possibility of utilizing a TLS-based method in non-destructive assessment of stem biomass. According to our results, biomass models based on forest-grown trees result in biased branch and stem biomass estimates for semi-open-grown urban birch trees. In general, the models overestimated the stem biomass and underestimated the branch biomass. However, when combined into total AGB the errors cancelled each other out. We found evidence that using TLS-derived tree volume and species-specific basic density can provide a feasible solution for stem biomass assessment. Of the three methods tested, the TLS-based method resulted in the most accurate estimates of stem biomass. Still, in order to achieve a field reference for tree AGB, the TLS-based method should also provide estimates of branch biomass. Because of the poor quality of the data, the proposed TLS-based method could not provide estimates of branch biomass. Hence, the quality of TLS data and the methods required for assessing branch biomass from it should be addressed in future studies. Also, similar studies should be performed in different urban surroundings covering a broader range of species and sizes of trees.

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Appendices

Appendix 1

Individual models for birch biomass components (Repola, 2008):

Total AGB: $\ln(R_{tot}) = b_0 + b_1 \frac{d_{Ski}}{d_{Ski}+12} + b_2 \frac{h_{ki}}{h_{ki}+22} + u_{5k} + e_{5ki},$

Stem wood biomass: $\ln(R_{stem\ wood}) = b_0 + b_1 \frac{d_{Ski}}{d_{Ski}+12} + b_2\, ln(h_{ki}) + u_{1k} + e_{1ki},$

Stem bark biomass: $\ln(R_{stem\ bark}) = b_0 + b_1 \frac{d_{Ski}}{d_{Ski}+12} + b_2 \frac{h_{ki}}{h_{ki}+20} + u_{2k} + e_{2ki},$

Living branch biomass: $\ln(R_{living\ branch}) = b_0 + b_1 \frac{d_k}{d_k+16} + b_2 \frac{h}{h+10} + u_{3k} + e_{3ki},$

Dead branch biomass: $\ln(R_{dead\ branch}) = b_0 + b_1 \frac{d_k}{d_k+16} + u_{4k} + e_{4ki},$

Foliage biomass: $\ln(R_{foliage}) = b_0 + b_1 \frac{d_{Ski}}{d_{Ski}+2} + u_{6k} + e_{6ki},$

where d_{ki} is the DBH (cm), d_{Ski} is 2 + 1.25 * DBH (cm), and h_{ki} is the tree height (m). For fixed parameters b_x and random parameters u_x and e_x, see Repola (2008).

Appendix 2

Model form of the individual models for birch biomass components (Muukkonen, 2007):

$\ln(BM) = \beta_0 + \beta_1 \frac{DBH}{DBH+\beta_2},$

where DBH is the tree diameter at breast height (cm) and β_0, β_1 and β_2 are biomass component-specific parameters (see, Muukkonen, 2007).

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